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A Framework for Intelligent Collaborative Enterprise Systems. Concepts, opportunities and challenges

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A Framework for Intelligent Collaborative Enterprise Systems

Concepts, opportunities and challenges

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Abstract. This paper presents a framework for Intelligent Collaborative Enterprise Systems (ICES) and discusses its evolution in the world of Big Data and Artificial Intelligence (AI) technologies for Decision Making (DM). The premise of this paper is to demonstrate the need for enterprise systems to evolve from being data and information oriented to intelligence sharing systems capitalizing on modern-day technologies of AI and machine learning. A collaborative enterprise system results from sophistication in communications technologies combined with vastly dispersed big data and its accompanying analytics. Collaborations within an enterprise system framework comprise multiple Cloud-based big data storages, sourcing of data from end-user IoT devices and back-end servers, storage and security of data, execution of business processes across multiple organizations and offering Analytics-as-a-Service to the users and consumers. Furthermore, the intelligence within these collaborations utilizes machine learning algorithms to provide continuous optimization and efficient decision-making processes for the entire enterprise eco-system. The outcome of our study is the delineation of a conceptual framework examining key elements that comprise ICES. We analysed the evolution of ICES, and how big data and its analytics based on techniques of artificial Intelligence improves decision making and prediction. We have outlined concepts and challenges of the conceptual framework implementation.

Key words: Intelligent Collaborative Enterprise Systems (ICES), Enterprise Systems Framework, Big Data, Artificial Intelligence, machine learning, business applications, business processes.

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1 Introduction

A fundamental change permeates enterprise systems of today. Typical enterprise systems vendors (such as SAP, PeopleSoft and Oracle) offer solutions comprising data, processing algorithms and interfaces (Xu 2011). The alternative to these enterprise systems is in-house developed systems which also contain data, processes and algorithms—albeit with greater customization and lesser configuration than the packages. These systems and contents have been supporting a specific enterprise that owned them (Ignatiadis and Nandhakumar 2009). With the rapid advances in technologies, especially the communications technologies of the Internet, a major change is shaping the future of these enterprise systems (Hustad and Olsen 2014; Madni and Moini 2007). The most fundamental of these changes in the Enterprise Resource Planning (ERP) solutions is there is no longer a singular entity responsible to serve a singular organization with well-defined physical and electronic boundaries. The impact of emerging technologies of the Internet, storage and analytics is that the business models that are supported by these ERP systems are undergoing change through digitalization (Elragal and Haddara 2012; Jagoda and Samaranayake 2017). The change popularly called digital transformation in organizational structure and behavior is the result of globally dispersed markets as well as high sophistication in communications and networking technologies (Henriette et al. 2016). Organizational boundaries are increasingly porous and customer demands are highly distributed and global. Collaboration, rather than competition, seems to be the basis of sound business strategies in an interconnected, digitally savvy world. This business strategy needs to be supported by and reflected in the modern day enterprise systems; furthermore, its alignment with enterprise systems capabilities is still a challenge that needs addressed (Arntzen Bechina and Ndela 2009; Rho and Vasilakos 2018).

Figure 1 illustrates an example of collaborations within an enterprise systems framework. This framework comprises multiple Cloud-based data storages, sourcing data from end-user IoT devices and other back-end servers, storage and security of data, execution of business processes across multiple organizations and offering of Analytics-as-a-Service to the users and consumers. As the volume of data increases together with its velocity—particularly with the IoT sensors—it moves in the realms of big data.

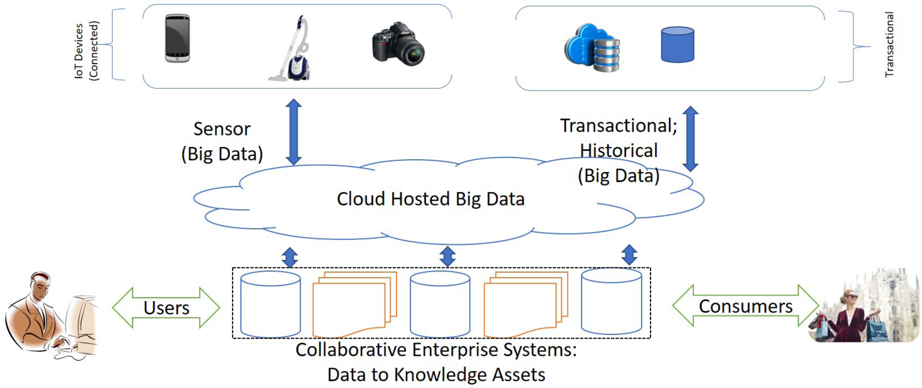

Figure 1: An example of collaborative Enterprise Systems sourcing IoT sensor data, other organizational data and internal/external information

A simple example of the aforementioned change is selling an airline ticket. Consider the level of collaboration needed in selling that airline ticket in today's market. An airline rarely sells only an air ticket. Instead, the airline wants to sell a flight ticket along with car rental, travel insurance and hotel stay. This package sale requires multiple external organizations such as car rental companies and hotels to collaborate with each other. Therefore, their corresponding enterprise systems also need to collaborate—resulting in an eco-system of Collaborative Enterprise Systems (CES) (Davenport 1998; Eldar et al. 2010; Razavi et al. 2010). Thus, the changes in the business environment and its needs and opportunities require a high level of interoperability enabling knowledge flow and data processing performed in an optimized way. CES provide specialized services with a level of intelligence so that automated learning can happen (Zhang et al. 2018). CES are not merely exchanging data and information with partnering organizations using protocols and databases. CES represents multiple systems, applications and databases that are continuously collaborating with each other in a dynamically changing environment. The technical policies and business procedures with CES need a phenomenal amount of inbuilt intelligence in order to automate the collaborations (Birgersson et al. 2016; Mirel B. et al. 2009). For example, a CES framework enables a medical insurance company to dynamically source data on hospital admissions and correlate it with patient demographics. As a result, the insurance company has the potential for a reduction in insurance costs for a certain cross-section of its clients. In the the airline example, the airline provides car and hotel facilities to its passengers and also correlates publicly available traffic with weather information in order to provide personalized and optimized schedules for passengers depending on their purpose of travel (e.g., family visit, business visit, or medical emergency).

This collaboration-driven scenario leads to some interesting problems that are worth investigating. These challenges include the need for a business to trust other collaborating businesses and for its collaborating systems to decide within a very short time whether to execute or reject a process-call. The need to base systems decisions on previous decisions (essentially Machine Learning algorithms), suggest additional collaborative opportunities between businesses, to ensure each transaction between two or more collaborative systems is legally compliant and to ensure that the systems are cyber-secure are additional challenges. While the list could be extensive, the potential problems can be summarized into a single need for undertaking a fine, balancing act in decision-making by each of the collaborating organizations. Thus, the problem or challenge of modern-day collaborative enterprise systems is to incorporate intelligence that enables fine-granular decision-making and make predictions using machine learning algorithms. Optimization of these services requires integration of vast amount of big data available within and outside of the organization (Birgersson et al. 2016). The sourcing of such data through third-parties, government agencies and data vendors, and processing it to improve business decision-making is going to be critical for successful Intelligent CES (ICES). In the airline example, the airline also needs to be fully aware of the availability of hotel rooms and cars at a particular location before it can offer the package to a traveler. The need for interconnectedness amongst the underlying systems is paramount. Furthermore, there is a need for those underlying systems to support decision-making based on sophisticated analytics utilizing large amount of widely dispersed data (Jan et al. 2019; Ruchi and Srinath 2018). Big Data and Machine Learning algorithms are the key technologies to help manage and harness large amounts of rapidly changing data. Several research studies have explored the potential of big data in decision support systems in different domains such as in healthcare, or supply chain, (Fredriksson 2018; Jeble and Dubey 2018; Sagiroglu and Sinanc 2013). Some other studies have also investigated the role of big data in ERP systems (Elragal 2014). There are also investigations in the role of big data and machine learning in supporting decision making in enterprise systems (Davenport 2018; Duan et al. 2019). These studies need to be assimilated and extended in order to identify the key elements for a generic framework for ICES. What are the business rules and governance standards for an organization to move toward an intelligent collaborative Enterprise Systems? What are the challenges in implementing and operating such collaborative systems? This exploratory study intends to outline a framework for ICES that enables AI-based decision-making which improves the quality of collaboration and tackles the problems mentioned above. The AI-based ICES can *learn* from previous decisions made through collaborations, and suggest improved decisions based on machine learning algorithms while using big data. Such AI based ICES also results in risk reduction for businesses through compliance, documentation and traceability. The rules and standards to support organizations in moving toward an Intelligent Collaborative Enterprise Systems are also discussed in this paper.

The next section outlines the literature on various collaborative levels in an Enterprise system with the aim of positioning intelligence at the right level. Section 3 outlines the basic literature on big data, machine learning and deep learning, from the point of view of utilizing these concepts in an intelligence CES. Section 4 outlines the mostly qualitative research methodological approach. Section 5 describes discovering of the dynamics of ICES and the penultimate section, before conclusions, is the discussion around the framework for an Intelligent Collaborative Enterprise System including the associated rules, governing standards, challenges and risks.

2 Literature on levels of collaborations in Enterprise Systems

Collaboration is a fundamental shift in business values and strategies, and needs to be supported by corresponding enterprise systems. Collaboration implies two or more organizations working together to create a business advantage through information sharing and joint decision-making. The sharing occurs through automation of business processes (Rho and Vasilakos 2018). Enterprise systems are required to make creative use of data and information within the organization in a way that results in new bodies of knowledge that can be applied in practice (Xu 2011). Collaborations within enterprise systems develop incrementally—from data to information, and then business processes, knowledge creation and utilization. Eventually collaborations enable intelligence across multiple business organizations. Based on our experience in the banking sector and literature reviews, an evolution of enterprise is depicted in Figure 2.

Data. Level 1 is the basic sharing of data across organizations. Without sharing, data would be repetitive and redundant. For example, a customer demographic data, such as name and address, is usually stored by the telephone company. Therefore, this data need not be stored by the bank. Instead, this data is collaboratively available to the bank from the telephone company under contracts. Sharing data through well-connected, reliable, and trustworthy partners is the basic form of collaboration among organizations. A

CES needs to incorporate data sharing is usually over the Cloud in order to facilitate collaborations.

Information. Level 2 represents the next level of sharing information, in a generic way so customer behavior is also personalized. For example, the bank now provides information on demographic behavior patterns, such as spending styles, income groups, and geographical nuances (e.g., near beach or hills, next to a large sporting arena), to the telephone company. Once again, this occurs under contracts between two (or more) businesses collaborating with each other through CES. Data Analytics play major role here in creating information and understanding the paths of decision-making based on the information between the businesses.

Process. Level 3 uses process models which by sharing activities and steps undertaken by the businesses in achieving a common business goal. For example, the process of opening an account in a bank or withdrawing cash from an ATM is largely similar in all banks across the globe. While minor variations in each of these processes is accepted, the fundamental process remains the same. By creating and uploading a basic process model for opening an account, it is possible for other banks to share that process model. Rules and regulations can be commonly applied to these collaborating banks as well. Furthermore, agencies specializing in fraud-detection can collaborate with the bank's system for suspicious transactions.

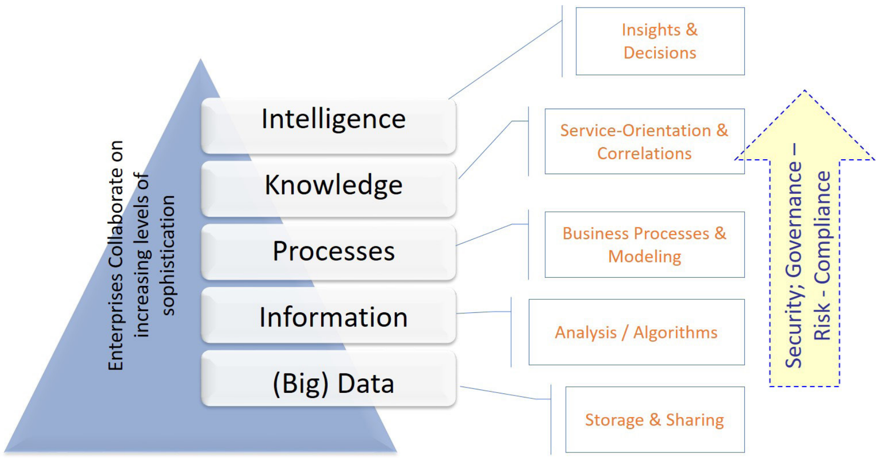

Figure 2: Increasing levels of collaborations in Enterprise Systems—fro data to intelligence

Knowledge. Level 4 shares knowledge about an individual or a group of customers or users across multiple organizations. For example, correlation between the information about a customer (person) available to one organization and h other bits of information (such as geographical location or spending habits) available to another organization, can be established. These wide-ranging correlations produce new and unique knowledge about that customer that was not possible with direct, single-organization analytics. Intelligence using big data can even extend the predictability of behavior beyond one customer to an entire customer group.

Intelligence. Level 5 is the fully mature implementation of collaboration by a group of organizations aiming at a common goal. This common goal is to enhance the customer experience in the most effective and efficient way. Customer groups can act in a collaborative manner to achieve higher value for themselves. Collaborations are not limited to a single organization but, instead, require exchange of data and information across highly porous electronic boundaries of modern-day organizations.

Collaborations create and synergize intelligence within and across multiple organizations to produce *actionable insights* to the collaborators. Intelligence can be garnered through information technologies that generate new and dynamic knowledge within the organization. This intelligence is achieved by correlating seemingly unrelated pieces of information that may be residing in silos. Knowledge, which comes from correlating the information silos, provides insights to the users for appropriate application. This application of knowledge is known as Business Intelligence (BI) (Duan and Xu 2012). Many contemporary enterprise systems utilize the concept of BI to source, extract, process and display data (Chen et al. 2012). BI, however, is a narrower view of the utilization of intelligence by businesses; collaboration amongst a group of businesses requires a concept called Collaborative Intelligence (CI) (Tiwary and Unhelkar 2015). CI in CES envisions a broader view that leverages collaboration and information sharing across multiple organizational boundaries and in a dynamic manner.

A challenge in a Collaborative Intelligence environment is that not only should the data, information, process, and knowledge be shared, but they should also be made available at the right time and place for the participating organizations. There is a need for an integrated and *intelligent* CES—right from data hubs and warehouses through to operational processes—that enable electronic collaborations. These electronic collaborations are enabled through tools and technologies (typically Web Services and also, increasingly, Analytics-as-a-Service) (Yeow et al. 2018). Collaborative Intelligence (CI) aims to solve the challenge of enabling multiple organizations to share data, information, processes and knowledge in a timely and efficient fashion. CI enhances BI capabilities for collective value and to ultimately reduce costs. Collaborations create and synergize intelligence within and across multiple organizations to produce actionable insights for users or end customers. The growing interest in Artificial Intelligence techniques suggests an important role in rejuvenating enterprise systems. Thus, we define Intelligent Collaborative Enterprise Systems (ICES) as systems encompassing sub-systems, large amounts of heterogeneous data, information, people, technologies, diverse applications and processes. ICES is also poised to play a role in supporting the digital transformation of enterprise by utilizing Machine Learning, which is necessary to analyze big data that is prevalent in such enterprise systems. We foresee some interesting opportunities of such systems by addressing a whole range of innovative applications. At the same time, it is important to identify the challenges that might hamper further development of ICES. One of the ICES requirements is to provide specific mechanisms to handle the dramatic growth of data in different formats and size. Big data mining is similar to data mining but the scale of big data is much larger (Huei Lee et al. 2014). Big data challenges include storing and analyzing large, rapidly growing, diverse data stores, then deciding precisely how to best handle that data (Kaisler et al. 2013).

The next section describes basic concepts of big data and techniques from artificial intelligence with a special focus on machine learning and deep learning. The impact on intelligent collaborative enterprise systems is also outlined.

3 Literature on big data, machine learning and deep learning

3.1 Big data

Big data is essentially data, further characterized by high Volumes, high Velocity and myriad Variety laced with Veracity. These are the popular Vs of big data. A learning organization goes beyond using the inherent characteristics of Big data by discovering the hidden Value (IBM). This is the fifth V in the characteristic of Agile business decision making as it results in value to the business and to the customer (Unhelkar 2017). McKinsey defined big data as "large pools of data that can be captured, communicated, aggregated, stored, and analyzed." (Manyika et al. 2011). This description appears to be more appropriate for large, historical static data sets. Data are anything but static (Unhelkar 2016). Therefore, as the data increases in size and reaches the volumes of big data, it is actually a combination of both static (large volume) data as well as the rapidly changing, dynamic data (high-velocity) such as data being streamed from IoT devices.

Big data as a discipline includes observations, analyses, conclusions and insights. Big data is defined as "high-volume, high-velocity, and/or high-variety information assets that require new forms of processing to enable enhanced decision making, insight discovery and process optimization" (Günther et al. 2017). Large bodies of data also have encrypted patterns that represents knowledge (Unhelkar 2010) preserved from the past and providing invaluable hints, tips, and even concrete solutions to challenges being experienced in the present.

Success with technologies provided by vendors first requires an effort to understand the business problem. This is one of the crucial differentiators in a strategic approach incorporating big data in ICES. Analytics in big data are important but not without proper understanding of business (based on (Sivarajah et al. 2017)).

A crucial differentiator in big data analytics is its granularity. The technologies associated with big data enable corresponding analytics to drill down to the finest level of detail (Bibri and Krogstie 2017). This analytical capability is important because the higher the velocity of incoming data, the greater is the resource requirements to process that data within a short time span.

The technologies associated with big data are considered disruptive because they have the potential to dramatically change business. This change occurs in both the macro and micro business environments. While machine learning can help harvest knowledge, as the data gets bigger and arrives faster, predictive analytics solutions based on deep learning come into play (Chen and Lin 2014). Deep learning techniques, supported by computational power, play a crucial role in knowledge discovery (Chen and Lin 2014).

3.2 Machine learning

Machine Learning (ML) techniques provide opportunities to tackle a wide range of complex problems (Madani et al. 2017). ML is embedded in tools that express domain of expertise (Shalev-Shwartz and Ben-David 2014). A good set of assumptions enable easier and faster learning processes. Machine learning algorithms are based on statistical analysis, and provides mechanisms for software applications to predict outcomes without being explicitly programmed (Rouse 2011). Machine learning provides tools to learn from data and provide data driven insights, decisions, and predictions (L'Heureux et al. 2017). Machine learning is seen as an algorithm that builds computer applications that automatically improve with past experience (Ayodele 2010; Carbonell et al. 1983). ML is ideally applicable for tasks that are far too complex to program and where there is a need for the systems to learn and improve based on previous learning pattern through some experience. Machine learning is best used within a changing environment (Shalev-Shwartz and Ben-David 2014).

Learning occurs in the enterprise systems in different ways. The learning paradigms for machines are most commonly grouped into supervised and unsupervised learning. These learning paradigms are understood as follows:

Supervised learning: This is the algorithm that takes sample input and corresponding expected output and learns from that relationship. As a simplified example, consider the sum of two numbers, 2 and 3 with the result 5. The algorithm learns to add any two given numbers; so, when provided with another set of numbers, say 4 and 6, the result is computed as 10. Alternatively, the algorithm can be taught to find the missing number if only one input and the result is provided (e.g., a number 2 is provided and a result 5, then the missing number is 3). Supervised learning can play a significant role in CES as systems from multiple, collaborating parties can be *taught* based on previous decisions to undertake similar decisions in shorter time. CES can also be taught to flag exceptions in decisions for human intervention.

Unsupervised learning: Here the algorithm is not specified with the addition; instead, the three numbers are simply made available—2, 3 and 5. The algorithm develops its own logic in order to discern that when 2 and 3 are added, the result is 5. This learning can be verified over a massive data set running into billions of records. Without the technologies that support big data, this computation was not possible, as it requires substantial computing power in a distributed architecture. The learning algorithm here discovers hidden patterns that can help users consider the possibility of new questions. It is thus learning to learn based on the discoveries in initial iterations. CES can be exposed to databases containing vast amounts of data and made to come up with *themes* around that data. While the CES themselves may not be able to initially identify what these themes imply, later, as the interpretation is fed into the systems, the unsupervised identification of theme leads to an increasingly well-defined interpretation of the themes. This ability of machine learning to dive into vast amount of data that would not make sense to a regular ERP solution is important in order to incorporate intelligence in CES.

3.3 Machine learning and big data

How can machine learning foster business decision-making that is an important feature in CES? Data is central to decision-making in several domains of applications. For example, analysis of data is applied extensively in many domains such as banking (Weng et al. 2006), industrial quality control (Da Cunha et al. 2006), predictive maintenance

(Liulys 2019)) and even in elections (Havenstein 2006; Zolghadr et al. 2018). Knowledge discovery and data mining have been investigated by various authors (Cabena et al. 1998; Grossi et al. 2017; Schmidt and Sun 2018).

The knowledge discovery processes are categorized under six distinct groups (Helmy et al. 2018) as shown in Figure 3: Formulating the Domain Application, Data Acquisition, Data Preparation, Machine Learning, Evaluation and Knowledge Discovery and Deployment.

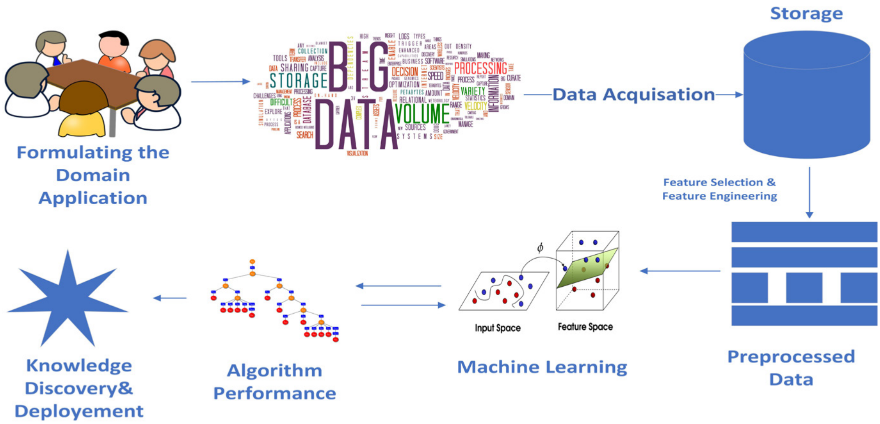

Figure 3: Knowledge discovery/deployment process

ML is integral to this knowledge discovery process within big data. There are three categories of machine learning (Robert 2014); supervised learning, unsupervised learning and reinforcement learning (Witten et al. 2016). Supervised learning algorithms predict a value based on existing historical data using regression and classification. When the target class is a set of discrete values, then it is a classification task; when they are continuous numerical values, then it is a regression task (Fawcett and Provost 1997) (Enke and Thawornwong 2005). Examples of classification tasks are whether a customer will remain loyal to the company or not (Wei and Chiu 2002).

In unsupervised ML, the algorithms find patterns in data without having any prior knowledge of the dataset (Müller and Guido 2016) (Brachman et al. 1996). Quality of data representation is important in order to ensure good performance on the learned patterns. Features can also be automatically extracted without direct human input. ML, especially unsupervised, finds patterns in data without having any prior knowledge of the dataset (Müller and Guido 2016) (Brachman et al. 1996).

Deep learning is playing an increasing role in big data predictive analytics approaches (Chen and Lin 2014). Deep learning uses supervised and unsupervised strategies to learn multi-level representations and features in hierarchical architectures for the tasks of classification and pattern recognition (Zhang et al. 2018).

3.4 Exploration of the concepts of collaboration and reflection on the impact of big data and machine learning

The literature study around levels of collaborations and the technologies of big data and machine learning formed the basis of our discussions with fellow researchers and information technology (IT) professionals. Analysis of the documentation of these discussions and further exploration of the literature revealed the potential opportunities and challenges of using big data and machine learning in collaborative enterprise systems. Previous consulting experience and active reflections on those experiences provided opportunities to identify key elements of an intelligent collaborative enterprise systems and also its potential challenges and issues. The *intelligence* within CES needs to be verified and validated through decision-making in real life by collaborating organizations.

Table 1 documents the key concepts of collaborations in enterprise systems. These concepts form the basis of our exploration into the mechanisms for embedding intelligence within the CES.

In addition, our approach to the literature review focuses on the state of the art of enterprise systems, the role of intelligence within these systems and the ease of their collaboration. Research studies investigating challenges in using emerging technologies such as big data, machine learning for decision making and improvement in collaborative enterprise systems are also examined. We have adopted a descriptive overview of our literature. Our literature and exploration followed the method of: search, selection, analysis, and synthesis processes (Wee and Banister 2016). The result of our overall analysis leads the framework for ICES described in the following section.

4 Discovering the Dynamics of Intelligent Collaborative Enterprise Systems (ICES)

Intelligence can be garnered through information technologies that generate new and dynamic knowledge within and across the organization. Collaborative organizations interact with each other, their customers and suppliers in real-time through web services. In addition to the technical capabilities of software, these collaborations also require strong business relationship-building skills. These business relationships include

Key Concepts	*Description*	*References*
Collaborations	These are essential interactions between businesses (and their systems) in order to carry out business actions and achieve business goals which cannot be achieved by a single business.	(Peters et al. 2010; Ravikumar et al. 2019; Shafiei and Sundaram 2004) (Rho and Vasilakos 2018)
Enterprise Systems	These are software systems supported by corresponding data that enable business organizations to carry out their key functions (e.g., sales, marketing, inventory management, accounting, HR). Enterprise systems are continuously evolving to incorporate the Cloud, Data Science, Artificial Intelligence and Mobility—together with Cybersecurity.	(Helmy et al. 2018; Henriette et al. 2016; Khan et al. 2014; Lomotey and Deters 2014; Manyika et al. 2011; Peters et al. 2010; Sathi 2012; Schmidt and Sun 2018; Sivarajah et al. 2017)
Artificial Intelligence & Machine Learning	Concepts and Algorithms that are implemented in order to capitalize on the abilities of software systems to learn in both Supervised and Unsupervised manners and continue to learn and correct themselves.	(Furman and Seamans 2019; Kotaro 2018; L'Heureux et al. 2017; Rouse 2011)
Big Data	High Volume, Rapid Velocity and Differing Varieties of Data that has the potential to be analysed using Data Science techniques in order to provide insights.	(IBM ; Khan et al. 2014; Oussous et al. 2018; Sagiroglu and Sinanc 2013)
Business Decision Making	Includes processes and procedures within business organizations that have the potential for ongoing improvement through the use of Intelligence based on (typically) Big Data.	(Babu and Sastry 2014; Dusanka and Aleksandar 2013)

Table 1. Key concepts of collaborations in Enterprise Systems

people skills and forming electronic policies that can be used in creating and executing electronic collaborations. Building relationships and collaboration also leads to closer scrutiny of the inner workings of member companies (Barekat M 2001) resulting in a need for a greater level of trust and mutual understanding between these clustering member companies.

We discovered that a CES framework needs to be a platform that facilitates direct information exchange amongst otherwise siloes applications (both within and outside of the organization). Internet-based exchanges resulting in sharing of information amongst those applications also needs to be facilitated within the CES (Figure 4). These information exchanges evolve into ontology-based collaborations among multiple applications and databases.

Furthermore, as highlighted in Figure 4, an organization needs to collaborate amongst its people and processes. Business value is derived by enabling people to make productive use of applications that goes beyond the specific transaction they are engaging in with the organization.

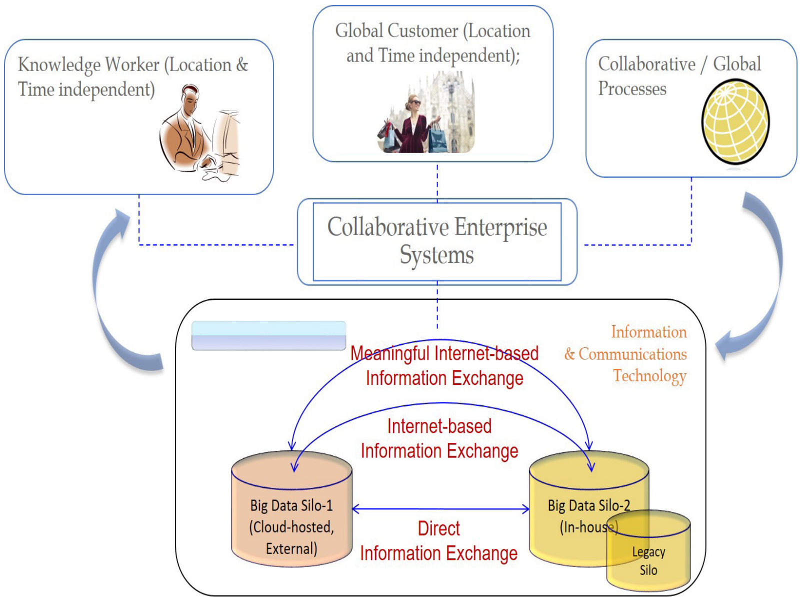

Figure 4. Collaborative Enterprise Systems interact with Knowledge Workers, Global Customers and Collaborative/Global Business Processes—all the time utilizing the Information and Communications Technologies to capitalize on the available Data (in-house and external)

Figure 4 shows the opportunity to create and share data and information across organizational boundaries. Such sharing can reduce rework and, at the same time, produce imaginative new pieces of knowledge that the organization can creatively use. Collaborative Intelligence (CI) is the extension and application of BI together with collaborative business process engineering, (Trivedi and Unhelkar 2009) which is built on Artificial Intelligence. CES, equipped with Machine learning, can optimize organizational resources by using current cloud computing and SOA capabilities (Gil et al. 2016).

For example, organization A, when interacting and sharing information with organization B, needs its systems to understand the corresponding systems of organization B. This includes services offered and consumed by organization B. The inter-organizational contracts, generic business rules, generic data format, and generic translation rules form part of the ontologies of these services. The sharing of services information is through contracts, public information business rules that are published and subscribed to on the cloud. The CES business rules also define what information can be stored and retrieved. For example, the information considered public for both organizational stakeholders, such as customers, is shared; information about suppliers is made available based on information access policies. When constructed carefully, such a collaborative effort does not compromise an organization's market position and could lead to enhancing the position.

The size and complexity of big data is such that building the models of solutions from Big data is not enough; tools are needed to handle the answers and also frame new questions. With Big data, business decision makers struggle to figure out what questions to ask. With the exponential growth in data, it becomes important to not only provide better answers to business questions, but also to help businesses understand what types of questions they must ask of their data.

Traditionally, businesses have a rough idea of what the problems are and what they did not know; with big data, however, both the problems and the possible hidden answers in the data mass are unknown. For example, business leaders can ask the data scientists (or equivalent roles) whether it is worth exploring customer demographics to figure out customer attrition or potential growth or another potential topic. Can the data itself give an indication of what can be asked of it? This is precisely where machine learning has a role to play.

Machine Learning algorithms can dive deeper into data in order to identify patterns that are not possible to discern with traditional analytical approaches. This is because of the multi-layered or tiered nature of hidden, vast amounts of data. Algorithms need to be created in a manner that creates learning through the execution and provides insights. Thus, machine learning is the dynamic use of algorithms, which provides a range of opportunities ranging from learned user behavior to dynamic cyber defense.

Machine learning algorithms are about to search through massive amounts of data to find relevant and interesting questions that the collaborative business can ask to improve its overall value proposition. Such crucial questions are the result of identifying insightful similarities and differences within a large, multidimensional data set that is related or connected with each other in a CES.

An ontology is a network of concepts within a given domain. Ontologies in the semantic web are organized by defining the concepts based on their attributes and types. A common, shared terminology goes a long way to define and interrelate the concepts. The network of relationships between the concepts gives rise to new knowledge and insights. This is precisely what big data analytics are meant to do. Ontologies need not be limited to defined data sets. Having a well-organized ontology for a given domain also makes it possible to absorb new data and information.

Figure 5 shows the tiers, or increasingly meaningful layers of interactions, which start with a direct link between otherwise siloed data stores—1 and 2. The software

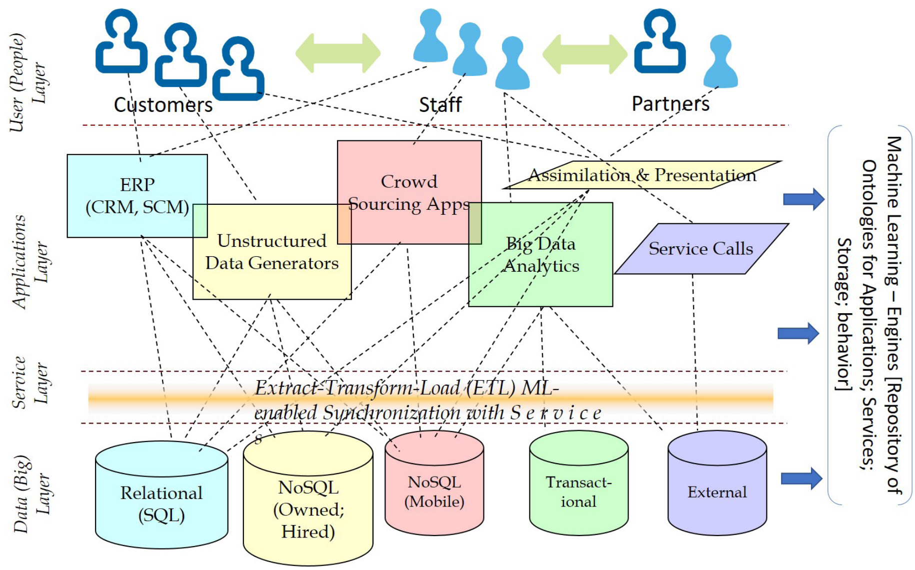

Figure 5. Synchronization of the various layers of a collaborative enterprise system: A big data/ machine learning perspective

enables increasingly meaningful exchanges based on rules, ontologies and taxonomies. The visuals support the interactions.

The rules and ontologies shown in Figure 5 are used to create a shareable knowledge base of data (e.g., customers) with common interests. For example, forming a customer group for a product (a car, boat or shoes) helps those customers share their knowledge around issues, concerns and quick solutions. Figure 5 further shows the disparate big data technology elements and their synchronization. The data, service, application and user layers are based on the technology architecture for CES. The service layer is the one that plays a major role in synchronizing these various elements.

Synchronizing the elements in Figure 5 has added challenge in the big data domain because the underlying distributed architecture also has to handle data that is rapidly changing. Synchronization of data needs to keep the operational (non-functional) parameters of the solutions in mind. This is because the synchronization limited to data is not going to handle the crucial performance parameters required of the big data application.

Synchronization has to also handle operational processes which continue to function while the data is being synchronized. This implies synchronization of data and also processes and presentation. Agile processes help bring together development and operations (DevOps) to ensure the new releases of analytics and applications are in sync with the existing application.

Synchronization is also required when it comes to the presentation layer (shown on top in Figure 5). The analytical outputs from structured and un-structured data are presented in a structured form. Analytics and presentations both need synchronization for presentation.

Synchronization of these architectural layers discussed thus far is not just a technical issue but also includes other aspects of a functioning organization such as people and processes. The layers shown in Table 2 are synchronized by use of Hadoop tools and processes which ensure applications and people are working together. Following are some of the factors to be considered in synchronizing the elements comprising enterprise technology layers:

1. Sources and availability of data including the ownership of data across enterprise systems and the process of collecting those data.
2. Affected business processes from incorporating big data analytics, and how the change needs to be managed (e.g., training of staff to start using the new processes).
3. Physical storage of the data and how compliance regulations apply to that data when it is synchronized.

Layers	*Big data technologies*	*Synchronization and Agility*
Data	HDFS; NoSQL	Use of Hadoop Tools to move data
Service	Models for the Analytical Algorithms (and Code Python, R)	APIs for plug in. Agile used to continuously test and promote services.
Application	CRM, SCM and in-house packages; based on HDFS, NoSQL and associated programming.	Structured and Unstructured data movement, conversion and integration for business processes. Iterative development of interfaces.
Presentation	Customers, Staff, Partners	Face to face collaboration between customers, staff and service providers. Presentations customized to suit user needs.

Table 2: Big Data Technologies and Agility

4. How long is the data current? Synchronization efforts are required only when the data that is synchronized has some currency in the decision-making process. Once the data is not current for decision-making, a process to remove it also needs to be initiated.
5. Should the synchronized data be stored separately (to obviate the need to do that synchronization exercise again) or should it be returned back to the original disparate sources after the processing is complete?

5 Discussion on ICES framework: rules and governing standards

Collaborations open up doors to an All-to-All business model. However, collaborations without requisite policies, guidelines and procedures present uncertainties and risks. This is because of the need for trust accompanied by electronic agreements (especially for service providers or vendors) in setting up and executing collaborations. The ICES framework aims to automate and manage clearly defined business rules and governance standards that define inter-organizational and public information usage. Following are some of the fundamental activities required of an organization as it moves towards Intelligent Collaborative Enterprise Systems:

Identifying like-minded organizations that are willing to collaborate by sharing data, information, and knowledge. Typically, this includes organizations within a given vertical line of business (e.g., travel, insurance, healthcare), although other combinations are also possible.

Establishing trust and agreements, both physical and electronic, which need to go beyond geographical boundaries and regions. This trust and these agreements also require setting up legal and compliance structures to safeguard the intellectual property of the collaborating organizations.

Engaging the global customer who is interested in a holistic end result and not in the individual processes that make up the end result. CI leads to creating services as well as creating customer groups that can form a dynamic structure to source and provide services within the collaboration.

Shared services library. The library provides each organization with a set of services that are used for the CI services. The current use of cloud computing in association with Web services are required to implement a shared services libraries. This can lead to consolidation of accounts, group dashboards, and predictive analytics for collaborating organizations.

Security framework. The security framework defines *what information* organizations share. This sharing is based on the business rules within and among the collaborating organizations. The information that specifically differentiates an organization from its collaborating partners is secured and not shared.

Generic business rules. These rules are based on industry standards and should be implemented in an organization-wide application framework. For example, generic business rules can be used to store and share location information of common customers. Initially, industry standards like ISO 9000 (for quality of service) can be used to store and share customer locations. Later, as the collaboration progresses, these rules may be modified and updated by the collaborators, while still adhering to the established external or commonly accepted standards.

Generic information translation rules. Information translation rules need to be established among collaborating partners. However, as the collaboration progresses, the frequency of dynamic translation of rules abates. This is so because, incrementally, the business rules come to be understood by the people and the systems that are interacting with each other across the various organizations' boundaries.

Consolidating CI information by identifying, defining, and sharing non-competitive information that would otherwise remain in silos and lead to repeated effort by individual organizations (e.g., customer demographic details). Organizations must obtain and implement processes and tools to keep the data and information current and reliable for use by all collaborators.

Implementing Web communications technologies (including Web services and corresponding service-oriented architecture) to make services available across the collaborating organizations.

Creating organizational dashboards that monitor the performance of multiple organizations rather than just the CEO dashboard for an individual organization. Such dashboards provide a succinct view of the collaborative effort.

Sharing lessons learned among collaborating organizations. This enables reduction of overall waste in terms of anticipating and solving problems, and can also have security and health implications. Some examples are sharing information about the spread of contagious diseases across borders and regions with other healthcare professionals or sharing the "sticky accelerator" problems of one auto manufacturer with other automakers. This lesson sharing in an intelligent way is true collaboration and can occur despite competition. The above approach to CI is based on extending an existing BI platform.

Innovative intelligent collaborative systems equipped with techniques from artificial intelligence aims to address limitations of traditional enterprise systems. Limitations include reducing human error of manually entered of data, identifying redundant data (from different database) and executing policies and contracts. Machine learning automates these processes and then applies continuous optimization to result in ICES. This also has challenges and risks that are discussed next:

Trust. Each organization needs to deposit information that is based on quality parameters and can be trusted by all collaborators. The organization also needs to comply with the withdrawal rules.

Timeliness of the information. Today organizations require information to be available all the time. Therefore, it is important for collaborating organizations to deposit information in a timely fashion.

Delivery of information. It is also important that information be delivered in a format consumable by the subscribing organizations. If the information requires multiple translations before it can be used, organizations will be reluctant to adopt CI.

Resources required to establish the CI platforms. Organizations will need to find a cost-effective approach to implementing CI. If the costs of CI are prohibitively expensive, organizations will revert to old BI.

Legislative and contractual framework. Collaborating organizations need to develop a framework to quickly define the contracts that is required for information sharing.

Security. The security of the published information needs to be defined collaboratively.

Rules for information sharing. Lack of uniform rules and legislation for sharing personal information also impedes the creation of CI. In different countries, legislation is different for personal information sharing.

Discriminating between competitive and collaborative information. This determination is crucial to the overall CI enterprise, and it can change from time to time and place to place.

6 Conclusions and future directions

This paper presented the key elements of an ICES framework together with a study of collaborations. The premise of this paper is that with increasing sophistication in communications technologies, organizations have the opportunity to extend their reach beyond their organizational boundaries. The new business organization is a federated entity that continues dynamic collaborations with each other. Such clusters of organizations are continuously sharing and reusing data, information, processes, and knowledge in order to collaborate rather than compete. This collaborative aspect of enterprise systems is highly benefitted by application of big data and machine learning. This is so because these newer technologies enable optimization of a highly meshed-up enterprise eco-systems by dynamically analyzing performances and ensuring security.

Future studies in this domain need to explore business collaborations amongst multiple horizontal and vertical axes. Such studies include exploration of the vertical business functions, such as sales and marketing, or collaboration across horizontal technological platforms. We plan to undertake these future studies using an interactive and incremental approach towards our research problem. Therefore, we plan to use action research to further validate the key elements of the ICES framework. Mobility is likely to play an even greater role in ICES study as it enables personalization and customization of services to the customer. Therefore mobility, together with cybersecurity and privacy of the data forms an important extension of our study of ICES.

References

Arntzen Bechina, A. A., and Ndela, M. N., (2009). Success Factors in Implementing Knowledge Based Systems. *Electronic Journal of Knowledge Management* (7:2): 211-218.

Ayodele, T. O., (2010). Introduction to Machine Learning. In: *New Advances in Machine Learning*, IntechOpen.

Babu, M. S. P., and Sastry, S. H., Big data and predictive analytics in ERP systems for automating decision making process, *IEEE 5th International Conference on Software Engineering and Service Science*, 2014, pp. 259-262.

Barekat M, M., (2001). Virtual-e-teams making e-business-sense. *Manufacturing Engineer*, (80:2): 66-69.

Bibri, S. E., and Krogstie, J., (2017). The core enabling technologies of big data analytics and context-aware computing for smart sustainable cities: a review and synthesis. *Journal of Big Data*, (4:1): 38.

Birgersson, M., Hansson, G., and Franke, U., Data Integration Using Machine Learning, *2016 IEEE 20th International Enterprise Distributed Object Computing Workshop (EDOCW)*, 5-9 Sept. 2016, 2016, pp. 1-10.

Brachman, R. J., Khabaza, T., Kloesgen, W., Piatetsky-Shapiro, G., and Simoudis, E., (1996). Mining business databases. *Communications of the ACM*, (39:11): 42-48.

Cabena, P., Hadjinian, P., Stadler, R., Verhees, J., and Zanasi, A., (1998). *Discovering data mining: from concept to implementation*, Prentice-Hall, Inc.

Carbonell, J. G., Michalski, R. S., and Mitchell, T. M. (1983). Machine Learning Part I: A Historical and Methodological Analy, *AI Magazine* (Vol. 4).

Chen, H., Chiang, R. H. L., and Storey, V. C., (2012). (2012). Business intelligence and analytics: From big data to big impact. MIS Quarterly: Management Information Systems, 36(4), 1165-1188. *MIS Quarterly: Management Information Systems*, (36:4): 1165-1188.

Chen, X., and Lin, X., (2014). Big Data Deep Learning: Challenges and Perspectives. *IEEE Access*, (2): 514-525.

Da Cunha, C., Agard, B., and Kusiak, A., (2006). Data mining for improvement of product quality. *International journal of production research*, (44:18-19): 4027-4041.

Davenport, T. H., (1998). Putting the enterprise into the enterprise system. *Harvard Bus. Rev.*, (76:4): 121-131.

Davenport, T. H., (2018). From analytics to artificial intelligence. *Journal of Business Analytics*, (1:2): 73-80.

Duan, L., and Xu, L. D., (2012). Business Intelligence for Enterprise Systems: A Survey. *IEEE Transactions on Industrial Informatics*, (8:3): 679-687.

Duan, Y., Edwards, J. S., and Dwivedi, Y. K., (2019). Artificial intelligence for decision making in the era of Big Data-evolution, challenges and research agenda. *International Journal of Information Management*, (48): 63-71.

Dusanka, L., and Aleksandar, K., (2013). The Impact of ERP Systems on Business Decision-Making. *TEM Journal*, (2:4): 323-326.

Eldar, S., Carsten, B., and Norbert, G., Enterprise systems ecosystem: A case study based comparison of software companies, *16th Americas Conference on Information Systems*, Lima, Peru,, 2010.

Elragal, A., (2014). ERP and Big Data: The Inept Couple. *Procedia Technology*, (16): 242-249.

Elragal, A., and Haddara, M., (2012). The Future of ERP Systems: look backward before moving forward. *Procedia Technology*, (5): 21-30.

Enke, D., and Thawornwong, S., (2005). The use of data mining and neural networks for forecasting stock market returns. *Expert Systems with applications*, (29:4): 927-940.

Fawcett, T., and Provost, F., (1997). Adaptive fraud detection. *Data mining and knowledge discovery*, (1:3): 291-316.

Fredriksson, C., (2018). Big data creating new knowledge as support in decision-making: practical examples of big data use and consequences of using big data as decision support. *Journal of Decision Systems*, (27:1): 1-18.

Furman, J., and Seamans, R., (2019). AI and the Economy. In: *NBER book Innovation Policy and the Economy*, S. L. a. S. Stern (ed.), University of Chicago Press, pp. 161-191.

Gil, D., Ferrández, A., Mora-Mora, H., and Peral, J., (2016). Internet of Things: A Review of Surveys Based on Context Aware Intelligent Services. *Sensors (Basel, Switzerland)*, (16:7): 1069.

Grossi, V., Romei, A., and Turini, F., (2017). Survey on using constraints in data mining. *Data Mining and Knowledge Discovery*, (31:2): 424-464.

Günther, W. A., Rezazade Mehrizi, M. H., Huysman, M., and Feldberg, F., (2017). Debating big data: A literature review on realizing value from big data. *The Journal of Strategic Information Systems*, (26:3): 191-209.

Havenstein, H., (2006). IT efforts to help determine election successes, failures: Dems deploy data tools; GOP expands microtargeting use. *Computerworld*, (40:45): 1.

Helmy, M., Arntzen Bechina, A., and Siqveland, A., Using Machine Learning for Identifying Ping Failure in Large Network Topology. E. C. Dr. Massimo Coppola, Daniele D'Agostino, Jörn Altmann, José Ángel Bañares, (ed.), *Economics of Grids, Clouds, Systems, and Services*, Springer International Publishing, 5th International Conference, GECON 2018, Pisa, Italy, September 18–20, 2018, 2018.

Henriette, E., Feki, M., and Boughzala, I., Digital Transformation Challenges *MCIS 2016 Proceedings. 33*, 2016.

Huei Lee, Kuo Lane, and Yang, J., The implications of big data for the enterprise systems for small businesses *The Proceedings of Worldwide Microsoft Dynamics Academic*, Atlanta, Georgia, USA, 2014.

Hustad, E., and Olsen, D. H., (2014). ERP Implementation in an SME: A Failure Case. In: *Information Systems for Small and Medium-sized Enterprises*, v. L. H. Devos J., Deschoolmeester D. (eds). Springer, Berlin, Heidelberg (ed.), Berlin, Heidelberg, Springer, .

IBM. Big Data Platforms, Tools, and Research at IBM.

Ignatiadis, I., and Nandhakumar, J., (2009). The Effect of ERP System Workarounds on Organizational Control: An interpretivist case study. *Scandinavian Journal of Information Systems*, (21:2).

Jagoda, K., and Samaranayake, P., (2017). An integrated framework for ERP system implementation. *International Journal of Accounting & Information Management*, (25:1): 91-109.

Jan, B., Farman, H., Khan, M., Imran, M., Islam, I. U., Ahmad, A., Ali, S., and Jeon, G., (2019). Deep learning in big data Analytics: A comparative study. *Computers & Electrical Engineering*, (75): 275-287.

Jeble, S., and Dubey, R., (2018). Impact of big data and predictive analytics capability on supply chain sustainability. *The International Journal of Logistics Management*, (29:2): 513-538.

Kaisler, S., Armour, F., Espinosa, J. A., and Money, W., Big Data: Issues and Challenges Moving Forward, *2013 46th Hawaii International Conference on System Sciences*, 7-10 Jan. 2013, 2013, pp. 995-1004.

Khan, N., Yaqoob, I., Hashem, I. A. T., Inayat, Z., Ali, W. K. M., Alam, M., Shiraz, M., and Gani, A., (2014). Big data: survey, technologies, opportunities, and challenges. *TheScientificWorldJournal*, (2014): 712826-712826.

Kotaro, T. (2018). *The Power of AI from an Economics Perspective*. Japan.

L'Heureux, A., Grolinger, K., Elyamany, H. F., and Capretz, M. A. M., (2017). Machine Learning With Big Data: Challenges and Approaches. *IEEE Access*, (5): 7776-7797.

Lomotey, R. K., and Deters, R. (2014). Analytics-as-a-Service (AaaS) Tool for Unstructured Data Mining, *Proceedings of the 2014 IEEE International Conference on Cloud Engineering* (pp. 319-324): IEEE Computer Society.

Madani, B., Alagi, H., Hein, B., and Arntzen Bechina, A. A., Machine learning for capacitive proximity sensor data, *Society for Process and Design* Alabama, USA, 2017.

Madni, A. M., and Moini, A., (2007). VIEWING ENTERPRISES AS SYSTEMS-OF-SYSTEMS (SOS): IMPLICATIONS FOR SOS RESEARCH. *Journal of Integrated Design & Process Science, vol. 11, no. 2, pp. 3-13, 2007*, (11:2): 3-13.

Manyika, J., Michael Chui, Brad Brown, Jacques Bughin, Richard Dobbs, Charles Roxburgh, and Byers, A. H. (2011). Big Data: The Next Frontier for Innovation, Competition, and Productivity. In McKinsey Global Institute (Eds.) Available from www.mckinsey.com/insights/business_technology/big_data_the_next_frontier_for_innovation

Mirel B., Eichinger F, Nair V, and M., K., Integrating automated workflows, human intelligence and collaboration.

Mirel B1, Eichinger F, Nair V, Kretzler M., *Summit Transl Bioinform.*, 2009, pp. 79-83.

Müller, A. C., and Guido, S., (2016). *Introduction to machine learning with Python: a guide for data scientists*, " O'Reilly Media, Inc.".

Oussous, A., Benjelloun, F.-Z., Ait Lahcen, A., and Belfkih, S., (2018). Big Data technologies: A survey. *Journal of King Saud University—Computer and Information Sciences*, (30:4): 431-448.

Peters, L. D., Johnston, W. J., Pressey, A. D., and Kendrick, T., (2010). Collaboration and collective learning: networks as learning organisations. *Journal of Business & Industrial Marketing*, (25:6): 478-484.

Ravikumar, K., Kumar, K., Thokala, N., and Chandra, M. G., Enterprise System Response Time Prediction Using Non-stationary Function Approximations, Springer International Publishing, Cham, 2019, pp. 74-87.

Razavi, A. R., Krause, P. J., and Strømmen-Bakhtiar, A., From business ecosystems towards digital business ecosystems, *4th IEEE International Conference on Digital Ecosystems and Technologies*, 13-16 April 2010, 2010, pp. 290-295.

Rho, S., and Vasilakos, A. V., (2018). Intelligent collaborative system and service in value network for enterprise computing. *Enterprise Information Systems*, (12:1): 1-3.

Robert, C. (2014). Machine learning, a probabilistic perspective: Taylor & Francis.

Rouse, M. (2011). Machine Learning Definition. from http://whatis.techtarget.com/definition/machine-learning.

Ruchi, S., and Srinath, P., Big Data Platform for Enterprise project management digitization using Machine learning, *2018 Second International Conference on Electronics, Communication and Aerospace Technology (ICECA)*, 29-31 March 2018, 2018, pp. 1479-1484.

Sagiroglu, S., and Sinanc, D., Big data: A review, *2013 International Conference on Collaboration Technologies and Systems (CTS)*, 20-24 May 2013, 2013, pp. 42-47.

Sathi, A., (2012). *Big data analytics : disruptive technologies for changing the game*, Boise, ID, MC Press.

Schmidt, C., and Sun, W. N., (2018). Synthesizing Agile and Knowledge Discovery: Case Study Results. *Journal of Computer Information Systems*, (58:2): 142-150.

Shafiei, F., and Sundaram, D., Multi-enterprise collaborative enterprise resource planning and decision support systems, *37th Annual Hawaii International Conference on System Sciences*, 5-8 Jan. 2004, 2004, p. 10 pp.

Shalev-Shwartz, S., and Ben-David, S., (2014). *Understanding Machine Learning: From Theory to Algorithms*, Cambridge University Press.

Sivarajah, U., Kamal, M. M., Irani, Z., and Weerakkody, V., (2017). Critical analysis of Big Data challenges and analytical methods. *Journal of Business Research*, (70): 263-286.

Tiwary, A., and Unhelkar, B., Enhancing the Governance, Risks and Control (GRC):Framework with Business Capabilities to Enable Strategic Technology Investments

. Ali H.Dogru, Radmila Juric and A. A. Arntzen, (eds.), *Society for Design and Process Science*, SDPS, Dallas, TX, texas, 2015.

Trivedi, B., and Unhelkar, B., Semantic Integration of Environmental Web Services in an Organization, *2009 Second International Conference on Environmental and Computer Science*, 28-30 Dec. 2009, 2009, pp. 284-288.

Unhelkar, B. (2010). *Agile in Practice: A Composite Approach*. Boston, USA

Unhelkar, B., (2016). Overcoming the Big Data Strategy Lacuna. *Cutter Executive Update, data Analitics & digital technologies Practice* (11:11).

Unhelkar, B., (2017). *Big Data Strategies for Agile Business* CRC Press, USA.

Wee, B. V., and Banister, D., (2016). How to Write a Literature Review Paper? *Transport Reviews*, (36:2): 278-288.

Wei, C.-P., and Chiu, I.-T., (2002). Turning telecommunications call details to churn prediction: a data mining approach. *Expert systems with applications*, (23:2): 103-112.

Weng, S.-S., Wang, B.-J., Chiu, R.-K., and Su, S.-H., (2006). The study and verification of mathematical modeling for customer purchasing behavior. *Journal of Computer Information Systems*, (47:2): 46-57.

Witten, I. H., Frank, E., Hall, M. A., and Pal, C. J., (2016). *Data Mining: Practical machine learning tools and techniques*, Morgan Kaufmann.

Xu, L. D., (2011). Enterprise Systems: State-of-the-Art and Future Trends. *IEEE Transactions on Industrial Informatics*, (7:4): 630-640.

Yeow, A., Sia, S. K., Soh, C., and Chua, C., (2018). Boundary Organization Practices for Collaboration in Enterprise Integration. *Info. Sys. Research*, (29:1): 149-168.

Zhang, Q., Yang, L. T., Chen, Z., and Li, P., (2018). A survey on deep learning for big data. *Information Fusion*, (42): 146-157.

Zolghadr, M., Niaki, S. A. A., and Niaki, S. T. A., (2018). Modeling and forecasting US presidential election using learning algorithms. *Journal of Industrial Engineering International*, (14:3): 491-500.